Augmenting Tennis Point Stochastic Modeling Utilizing Spatiotemporal Shot Data

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Roadmap

- Background & Inspiration
- Impact & Extensions
- Methodology
- Results
- Future Work
Inspiration

Expected Point Value (EPV). *Cervone et al. (2016)*
Inspiration

Expected Shot Value (ESV). Floyd et al. (2019)

ESV Validation. Floyd et al. (2019)
Expected Shot Value is:

• “How many points a player can expect to score [in a given point] based on the circumstances at the time of a given shot”
• Based on the idea that the relative positioning of players on a tennis court affects the outcome of a point
• Derived from a stochastic model (allows for variation moving forward in time)

Expected Shot Value is NOT:

• The win-loss probability for both players in a point
  • ESVs are independent between players, so the striker and returner ESVs are not expected to sum to 1 for an individual shot
  • Past information the model is built on is incomplete
Current tennis analytics is primarily high-level statistics (serve, error, and winner percentages, points won, etc.). These ignore a large amount of the information we can learn from a match, including player movement, exertion, and patterns.

Hawk-Eye recovers a lot of lost information. We can use player tracking data to determine the relative position of players on a court (per Floyd’s original methodology). We can also use information about speed, spin, and length of match to augment this methodology and explore variations of this model.
Our Goal

We want to extend the Floyd et al. model to better incorporate the depth of the data that Hawk-Eye offers.

We hope to more accurately model the underlying mechanics of and strategy of tennis.
Why Do We Care

Understand the Progression of a Tennis Point

See at what shots a player might have had an advantage, missed an opportunity, or mounted a comeback

Expected Shot Value over the course of a tennis point.
Floyd et al. (2019)
Why Do We Care

Identify Player Strengths and Weaknesses

Where does a player have the highest success rate, highest failure rate? How do they compare to an “average” player?

Expected Shot Value difference between a player returning a shot and the dataset average. Floyd et al. (2019)
Why Do We Care

Guide In-Match Strategy

Given the player locations, where should a player hit their next shot, where should a player move next? What shots are most effective in these instances?

Return Expected Shot Value for all zones equidistant to the player’s current striking position. *Floyd et al. (2019)*
Opportunities for Extension

Features to Incorporate
Shot Type
Shot Speed
Shot Spin

Concepts to Explore
Fatigue
Distance and Direction Ran
Momentum
**Terminology**

**Shot**: an individual state where one player strikes the ball to their opponent

**Point**: a series of shots, ends when a player cannot return the ball or the ball goes out of bounds

**Server**: the player who hits the first shot of the point

**Receiver**: the player who receives the first shot of the point

**Striker**: the player hitting the current shot in a point (not always the same as the server)

**Returner**: the player receiving the current shot in a point (not always the same as the receiver)
Data

USTA Data Source
Men’s and Women’s singles match data from the US Open between 2015 and 2018
PRJ: player positions (25 fps)
TRJ: ball location and trajectory
XML: shot characteristics

Data Post-Filtering
701 unique matches
366 players, 690 unique matchups
144,695 points (80% of original data)
473,401 shots (73% of original data)
1. Assigning Strike/Return States

In order to create a Markov Chain model and reduce computational complexity, the tennis court is divided into zones, and states are created from player locations at each shot (usually striker_zone - returner_zone)

i.e. the state of this shot would be 10-7
2. Assigning Strike/Return Categories

This is a description of the shot’s outcome/effect on the point, associated with a numeric weight representing expected benefit.

<table>
<thead>
<tr>
<th>Strike Category</th>
<th>Symbol (λ_{SC})</th>
<th>Weight (w_{SC})</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pure Winner</td>
<td>λ_{PW}</td>
<td>1.00</td>
<td>In-bounds strike which is not returned</td>
</tr>
<tr>
<td>Set-Up of Pure Winner</td>
<td>λ_{SPW}</td>
<td>0.75</td>
<td>Strike by winning player prior to λ_{PW}</td>
</tr>
<tr>
<td>Forced Losing Strike</td>
<td>λ_{FLS}</td>
<td>0.75</td>
<td>Strike by winning player prior to λ_{FLS}</td>
</tr>
<tr>
<td>Non-Impactful</td>
<td>λ_{NI}</td>
<td>0.50</td>
<td>Strike which does not fall into other categorizations</td>
</tr>
<tr>
<td>Set-Up of Opponent’s Pure Winner</td>
<td>λ_{SOPW}</td>
<td>0.25</td>
<td>Strike by losing player prior to λ_{PW}</td>
</tr>
<tr>
<td>Losing Strike</td>
<td>λ_{LS}</td>
<td>0.00</td>
<td>Strike which goes out-of-bounds or into the net</td>
</tr>
</tbody>
</table>

Table 1: Original Floyd et al. Strike Categories and Weights

<table>
<thead>
<tr>
<th>Return Category</th>
<th>Symbol (λ_{RC})</th>
<th>Weight (w_{RC})</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Returned Pure Winner</td>
<td>λ_{RPW}</td>
<td>1.00</td>
<td>Returned λ_{PW}</td>
</tr>
<tr>
<td>Returned Set-Up of Pure Winner</td>
<td>λ_{RSPW}</td>
<td>0.75</td>
<td>Returned λ_{RSPW}</td>
</tr>
<tr>
<td>Returned Forced Losing Strike</td>
<td>λ_{RFLS}</td>
<td>0.75</td>
<td>Returned λ_{RFLS}</td>
</tr>
<tr>
<td>Returned Non-Impactful Strike</td>
<td>λ_{RNIS}</td>
<td>0.50</td>
<td>Returned λ_{NI}</td>
</tr>
<tr>
<td>Returned Set-Up of Opponent’s Pure Winner</td>
<td>λ_{RSOPW}</td>
<td>0.25</td>
<td>Returned λ_{RSOPW}</td>
</tr>
<tr>
<td>Returned Losing Strike</td>
<td>λ_{RLS}</td>
<td>0.00</td>
<td>Returned λ_{LS}</td>
</tr>
<tr>
<td>Not Returned</td>
<td>λ_{NR}</td>
<td>0.00</td>
<td>Unable to return</td>
</tr>
</tbody>
</table>

Table 2: Original Floyd et al. Return Categories and Weights
3. Calculating Transition Probabilities

A matrix that describes the probability of going from the current strike state $u$ to the strike/return state $w$ on the next shot

$$P_{uw} = \frac{N_{uw}}{\sum_{w'} N_{uw'}}$$
4. Calculating Strike/Return Values

These variables quantify the expected number of points a player will receive based on how they’ve struck/returned the ball previous

\[ SV(\beta^S) = \sum_{\lambda_{SC} \in \Lambda_{SC}} w_{\lambda_{SC}} \frac{|S_{\beta^S,\lambda_{SC}}|}{|S_{\beta^S}|} \]

\[ RV(\beta^S) = \sum_{\lambda_{RC} \in \Lambda_{RC}} w_{\lambda_{RC}} \frac{|R_{\beta^R,\lambda_{RC}}|}{|R_{\beta^R}|} \]
5. Putting it Together

Player 2 returning from state 14-7

\( \frac{2}{9} \) of Player 1's strikes from 14-7 were direct losing strikes, \( \frac{1}{9} \) were direct winners.

\( \frac{6}{9} \) strikes continued the point: 1 went to 2-14 (Player 2 SV = 0.750), 2 to 6-11 (SV = 0.438), etc.

\[
ESV = \frac{2}{9} (1) + \frac{1}{9} (0) + \frac{6}{9} (0.750 + 2 \times 0.438) + \ldots
\]

\[
ESV(c_u) = \sum_{c_w \in C_{shot}} RV(c_w) P_{uw} + \sum_{c_w \in C_{end}} PV_S(c_w) P_{uw}
\]

if the player is the striker

\[
ESV(c_u) = \sum_{c_w \in C_{shot}} SV(c_w) P_{uw} + \sum_{c_w \in C_{end}} PV_R(c_w) P_{uw}
\]

if the player is the returner
2. Assigning Strike/Return Categories

This is a description of the shot’s outcome/effect on the point, associated with a numeric weight representing expected benefit.

By adjusting these categories and their respective weights, we are able to incorporate new features and assign different values to each type of shot.
Our Models

Models we Explored

Shot Spin
Shot Speed
Serve Speed
Shot Type and Spin (top right)
Estimated Neutral Shot Weight (middle right)
Speed and Spin (bottom right)

General Setup

Define additional shot categories

Weight beneficial shots as 0.05 higher than the baseline and detrimental shots as 0.05 lower
Ensuring a Linear Relationship

Floyd et al. graph the relationship between ESV and Win Rate to determine the validity of their models.

We create these plots by pooling shots based on ESV, and calculating win rate as the percentage of shots the striker won.

All our plots show a linear relationship, which tells us that these models do not warp the underlying point mechanics.

This also uncovers bins that are consistently above and below the trend line, and thus potential structures we are not capturing.
Correlation between Strike ESV and Win Rate

Due to a high baseline R-squared, we did not see a drastic improvement with any of our models.

Models that incorporate spin appear to have a higher correlation.

Most improvements were due to outlier shots (very high or low ESV) changing bins.

Moving forward can attempt a weighted R-square measure to reduce outlier effect.

<table>
<thead>
<tr>
<th>Model</th>
<th>Strike ESV $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shot Type + Spin</td>
<td>0.9820</td>
</tr>
<tr>
<td>Spin + Dropshot</td>
<td>0.9815</td>
</tr>
<tr>
<td>Spin</td>
<td>0.9814</td>
</tr>
<tr>
<td>Estimated Neutral Shot Weight</td>
<td>0.9762</td>
</tr>
<tr>
<td>Floyd et al. (Baseline)</td>
<td>0.9758</td>
</tr>
<tr>
<td>Serve Speed</td>
<td>0.9758</td>
</tr>
<tr>
<td>Full Speed</td>
<td>0.9756</td>
</tr>
<tr>
<td>Full Speed + Spin</td>
<td>0.9756</td>
</tr>
<tr>
<td>Non-Serve Speed + Spin</td>
<td>0.9755</td>
</tr>
</tbody>
</table>
Examining Residuals

ESV Bin [0.55, 0.65]

The data point for this bin consistently fell above the trend line for all our graphs.

This bin includes all the first serves in our data, and is dominated by this shot (of the 110,692 shots, only 6,636 are not serves).

Removing first serves raises ESV from 0.5670 to 0.5881 and drop win rate from 0.7106 to 0.6698, which is in line with the linear model (top figure, red point).

This suggests there is a more complex underlying structure around serves.

<table>
<thead>
<tr>
<th>Location State</th>
<th>Strike ESV</th>
<th>Number of Shots</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>0.5657</td>
<td>104056</td>
</tr>
<tr>
<td>2-5</td>
<td>0.5958</td>
<td>3</td>
</tr>
<tr>
<td>2-9</td>
<td>0.5719</td>
<td>102</td>
</tr>
<tr>
<td>2-11</td>
<td>0.6141</td>
<td>293</td>
</tr>
<tr>
<td>2-13</td>
<td>0.6339</td>
<td>150</td>
</tr>
<tr>
<td>3-2</td>
<td>0.5730</td>
<td>84</td>
</tr>
<tr>
<td>3-4</td>
<td>0.6375</td>
<td>5</td>
</tr>
<tr>
<td>3-9</td>
<td>0.6144</td>
<td>202</td>
</tr>
<tr>
<td>3-11</td>
<td>0.5888</td>
<td>240</td>
</tr>
</tbody>
</table>
Implicit Physical Factors

Due to the zoning system used in our model, aspects such as distance and direction ran by a player are already included.

We can isolate certain types of movement, then examine the distribution of shot category and mean weight to assess its benefit/detriment.

We can deepen this analysis by looking at mean ESV rather than mean shot weight.

<table>
<thead>
<tr>
<th>Movement and Zones</th>
<th>PW</th>
<th>SUPW</th>
<th>FLS</th>
<th>NI</th>
<th>SUOPW</th>
<th>LS</th>
<th>Mean Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline to Net: (9 – 11) → (1 – 8)</td>
<td>2072</td>
<td>489</td>
<td>900</td>
<td>785</td>
<td>592</td>
<td>1045</td>
<td>0.6212</td>
</tr>
<tr>
<td>Backcourt to Net: (12 – 15) → (1 – 8)</td>
<td>335</td>
<td>94</td>
<td>204</td>
<td>226</td>
<td>246</td>
<td>329</td>
<td>0.5112</td>
</tr>
<tr>
<td>Retreat: (1 – 4) → (9 – 15)</td>
<td>13</td>
<td>7</td>
<td>19</td>
<td>85</td>
<td>36</td>
<td>77</td>
<td>0.3544</td>
</tr>
<tr>
<td>Cross Court: 9 → 11 or 11 → 9 or 12 → 15 or 15 → 12</td>
<td>188</td>
<td>92</td>
<td>280</td>
<td>896</td>
<td>177</td>
<td>488</td>
<td>0.4523</td>
</tr>
</tbody>
</table>
Exploring Fatigue and Momentum

Hawk-Eye provides information about match length, shots per point, and how far a player runs over the course of a match.

We can also attempt to model streaks of points won or shots hit with an above-average weight to capture momentum.

Estimating Category Weights

Much like Floyd et al., we assign category weights subjectively based on our knowledge and assumptions of the sport.

Interesting findings could lie in the differences between estimated weights.
Questions?